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Neural Prostheses: Linking Brain Signals to Prosthetic Devices

Carlos Pedreira*, Juan Martinez* and Rodrigo Quian Quiroga

Department of Engineering, University of Leicester, Leicester, United Kingdom

*These authors contributed equally.

(Tel : +44-116-252-2872; E-mail: cp155@le.ac.uk)

Abstract: This paper discusses Neuroprosthetic applications for potential use by paralyzed patients or amputees. These systems require advanced processing of neural signals to drive the prosthetic devices using decoding algorithms. The possibility of predicting motor commands from neural signals are the core of neural prosthetic devices and along this line we show how it is possible to predict movement intentions as well as what subjects are seeing from the firing of population of neurons.

Keywords: Neural Prostheses, decoding, neuroscience, robotics, control theory.

1. INTRODUCTION

Millions of people are paralyzed or have suffered an amputation. Although these people can still see the object they may want to reach, for example a glass of wine, and can still process in their brains the specific commands to pursue this goal, the action cannot be completed due to, for example, a spinal cord injury or due to the fact that the arm has been amputated. Given that in most cases the brain of these persons is intact, the possibility of reading brain signals would allow the development of Neuroprosthetic devices, such as a robot arm that is driven by neural activity.

Reaching for an object involves a series of complex processes in the brain (see Fig. 1), from evaluation of visual inputs to motor planning and execution. Converging evidence from monkey neurophysiology has

shown that the posterior parietal cortex (PPC) is a key node in this process, being involved in different types of movement plans [1, 2]. In fact, the PPC lies between the primary visual areas in the occipital lobe and the motor cortex, thus having a privileged location for visuo-motor transformations. Given this evidence, as well as related findings from motor cortex, the question arises of whether it is possible to predict movement plans from the activity of these neurons. Several studies have shown that this is the case, and the possibility of such predictions encouraged researchers to work on the development of Neural Prostheses [1-10].

In this paper we describe in detail the main steps for Neuroprosthetic implementations. We start by describing how to process the data for extracting the activity of single neurons using spike sorting algorithms and continue with the description of decoding algorithms

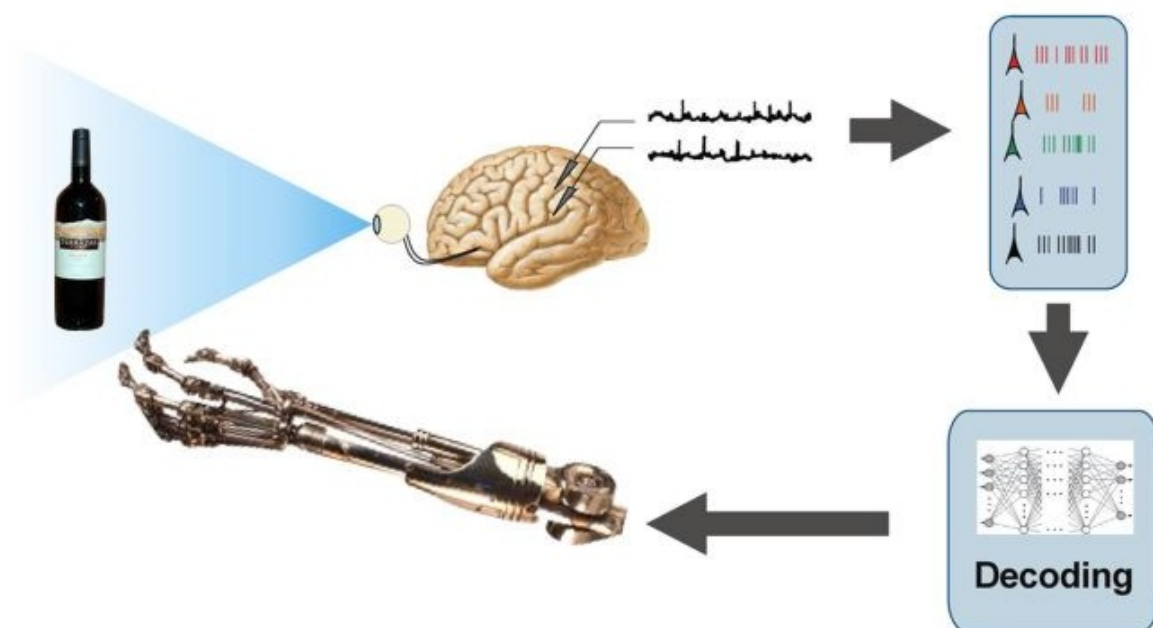


Fig. 1 Diagram of a neural prosthetic system.

used to predict movement intentions from the neural activity. These goal signals can then be used to drive the robotic devices. We also show two results in this direction. First we describe how it is possible to predict both arm and eye movements to different directions using recordings from the monkey PPC. Second, we show how from the activity of single neurons in the human hippocampus –such intracranial recordings are performed for clinical reasons in epileptic patients candidate to epilepsy surgery- it is possible to predict what the patients are seeing far above chance. The possibility of such predictions is a large step forward in the development of neural prosthetic devices.

2. NEUROPROSTHETIC SET UP

The core of neural prosthetics systems relies on the detection and processing of brain activity involved in the planning and execution of movement intentions [1, 2]. Fig. 1 presents a Neuroprosthetic setup, where a prosthetic limb controlled by the activity of different neurons, is used to reach an object. A first and crucial step in any neuroprosthetic system is to obtain reliable recordings from the particular area of interest. The interfaces for such recordings are constantly under development to provide long lasting recordings of good quality signals (see [12] for a review). Then, the recorded signals are processed using spike sorting algorithms (see next section for details), which allow the identification of the spikes of individual neurons. The activity of these neurons, in turn, provide the input to the decoding

algorithm (see Decoding section), which processes this data to send the information of the desired movement intention to the robot arm.

3. ANALYSIS OF NEURAL DATA

Using micro-electrodes inserted in the brain it is possible to record from neurons close-by the electrode tip and identify their activity using spike detection and sorting algorithms (see Fig. 2). For this, it is necessary to detect the firing of these neurons (i.e. the action potentials or ‘spikes’) laying on the background noise and then classify these spikes into different clusters –corresponding to putative single neurons- based on the similarity of the spike shapes [13]. In the last years, an automatic algorithm (Wave_clus) has been developed, which first performs the spike detection from the high-pass filtering the data, by setting amplitude threshold at:

$$Thr = 5\sigma_n \quad ; \quad \sigma_n = median\left\{\frac{|x|}{0.6745}\right\} \quad (1)$$

where x is the bandpass filtered signal and σ_n is an estimation of the standard deviation of the background noise (see [13] for details). Note that the estimation of equation (1) is based on taking the median of the signal and it is therefore locked to the noise level and is not dependent on the firing of large amplitude spikes, as when taking the conventional standard deviation of the

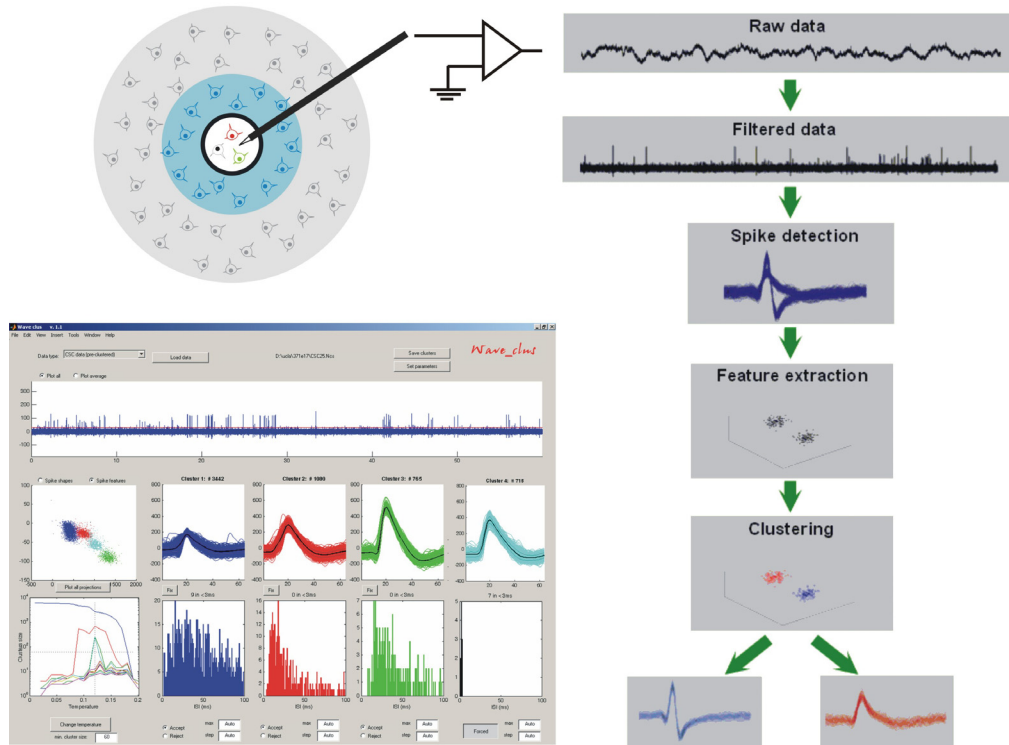


Fig. 2 Steps for Spike sorting and an example with a real recording.

signal. After spike detection, features or the spike shapes are extracted by using the wavelet transform, a time-frequency decomposition with optimal resolution both in time and frequency. Each obtained wavelet coefficient corresponds to a feature of the spike shapes at a given frequency and time range. The coefficients that best separate the signal are automatically selected by using a Kolmogorov-Smirnov test [13], choosing those with the least normal distribution, which likely represent more than one cluster of spike shapes. In the last step the algorithm does an unsupervised classification to group spikes into classes using “superparamagnetic clustering”, a clustering method from statistical mechanics that is based on nearest-neighbor interactions and does not assume any particular distribution of the data. It is important to remark that the whole method is unsupervised and fast, therefore being suitable for on-line implementations and to be used in neuroprosthetic applications.

Fig. 2 shows the output of Wave_clus for a recording in the hippocampus of one patient implanted with intracranial electrodes for clinical reasons. On top, the continuous data is displayed with the automatic threshold used for spike detection (in red). The bottom plots shows the 4 classified clusters of spike shapes and their interspike interval distributions, corresponding to the activity of different units around the tip of the recording electrode. The middle left plot shows the projection of all detected spikes in the two first wavelet coefficients chosen by the algorithm.

4. DECODING

Several approaches have been applied for the predictions of stimulus information or behavior using decoding algorithms. Nearest-neighbor decoders assign the different trials to the class of its respective nearest-neighbor in an n -dimensional space, where each coordinate corresponds to the firing of each of the n neurons. Alternatively, Fisher linear discriminant decoders introduce a dimensionality reduction (by projecting the original space where the classification is performed on to a line with a direction that maximizes the ratio of between-class to within-class distances) that optimally separates the samples of each class. Bayesian decoders use Bayes' theorem to identify how likely is for a specific stimulus s to be represented by a certain neural population response r as given by the posterior probability:

$$P(s|r) = \frac{P(r|s) \cdot P(s)}{P(r)}, \quad (2)$$

with

$$P(r) = \sum_s P(r|s) \cdot P(s), \quad (3)$$

where $P(s)$ represents the probability of presentation of s and $P(r|s)$ represents the conditional probability of obtaining a population response. The prediction of the most likely stimulus (s^P) is calculated from the posterior probability distribution by taking $s^P = \arg \max_s (P(s|r))$.

Fig. 3a shows the firing of two neurons in the medial temporal lobe of an epileptic patient implanted with

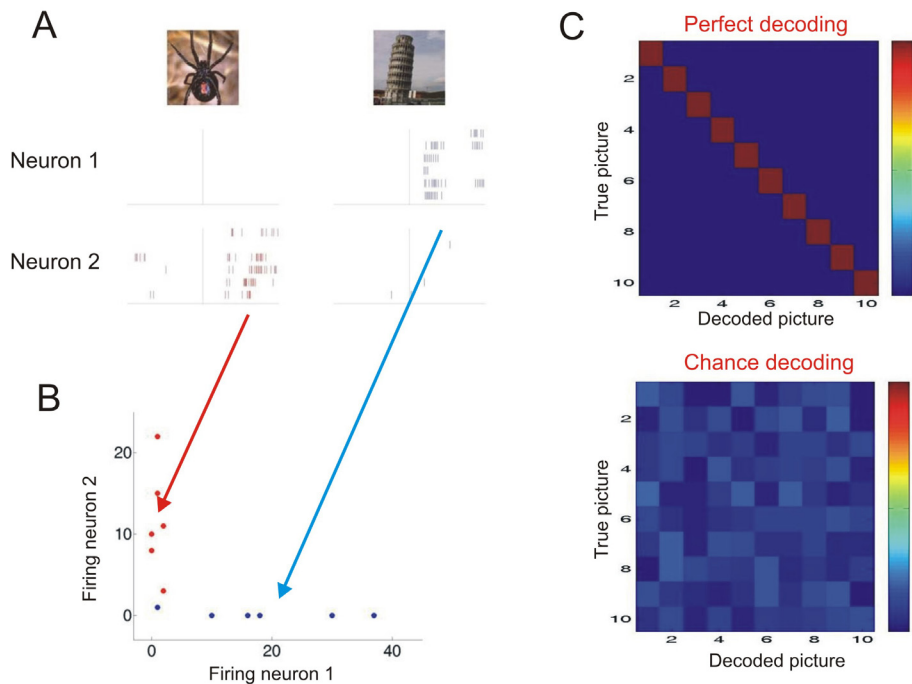


Fig. 3 Decoding algorithms.

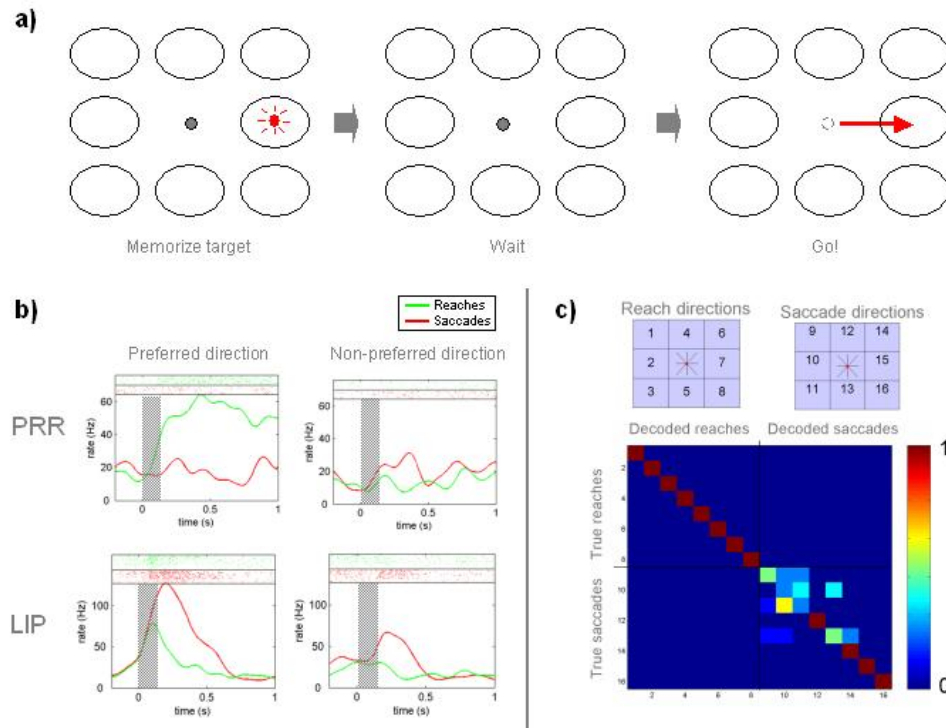


Fig. 4 Decoding of arm reaches and saccades using signals recorded from posterior parietal cortex (PPC) in monkeys.

intracranial electrodes for clinical reasons. Neuron 1 fires to presentations of the image of the tower of Pisa and neuron two fires to presentations of spider. Fig. 3b shows the firing of these two neurons for each picture presentation, giving two clusters of responses which are the input of the decoding algorithm. Perfect decoding is reflected by a diagonal with ones and zeroes everywhere else whereas a decoding at a chance level gives random entries in the confusion matrix (Fig. 3c).

5. PREDICTION OF MOVEMENT INTENTIONS

Fig. 4a shows the result of an experimental paradigm to test the possibility of predicting movement intentions based on the activity of neurons in the posterior parietal cortex in monkeys. During the experiment, a flashed target appeared in one of eight possible locations. After a waiting period, the monkey did a saccade or a reach, depending on the colour of the target. Fig. 4b shows the firing of a neuron in the Parietal Reach Region (PRR) –encoding arm reaches- and a neuron in the Lateral Intraparietal area (LIP) –encoding eye movements-, two anatomically segregates areas in the posterior parietal cortex. The raster plots are displayed on top of each panel and show the firing on the different trials, to the preferred and non-preferred location of each neuron (the location to which the neuron fired the most and the opposite one).

The neuron in PRR fired stronger to reaches than saccades and the opposite occurred for the neuron in LIP. This is consistent with the abovementioned evidence of the functional specialization in the posterior parietal cortex [2,10]. These responses, with different neurons

tuned to different locations, are the basis for the prediction of both the particular movement performed by the monkey (either a reach or a saccade) and its target location, and are in turn a key component of Neuroprosthetic devices. Fig. 4c shows the outcome of these predictions in the form of a confusion matrix, where the rows are the actual movements performed by the monkey and the columns are the predicted movements, using a decoding algorithm. As seen in the figure, decoding is perfect for reaches and close to optimal for saccades.

6. PREDICTION OF VISUAL INPUTS

Recent studies have reported the presence of single neurons with strong responses to visual inputs in the human medial temporal lobe [11, 14]. Given the selective firing of these neurons to the presented pictures, it seems in principle possible to predict which picture was shown each time. Fig. 5a shows the best five responses (out of a total of 114 pictures shown) of three simultaneously recorded units (out of 19 responsive units) during an experimental session. Unit 1 responded to pictures of animals and the actress Jennifer Aniston. Unit 2 responded to the basketball players Kobe Bryant and Shaquille O’Neil (both playing for Los Angeles Lakers back at the time the experiments were done). Unit 3 had strong responses for pictures of the actress Pamela Anderson. It is remarkable that units 1 and 2 were extracted from the same recording electrode placed in the left posterior hippocampus and their activity was separated after using the spike sorting algorithm described above. These units presented a completely

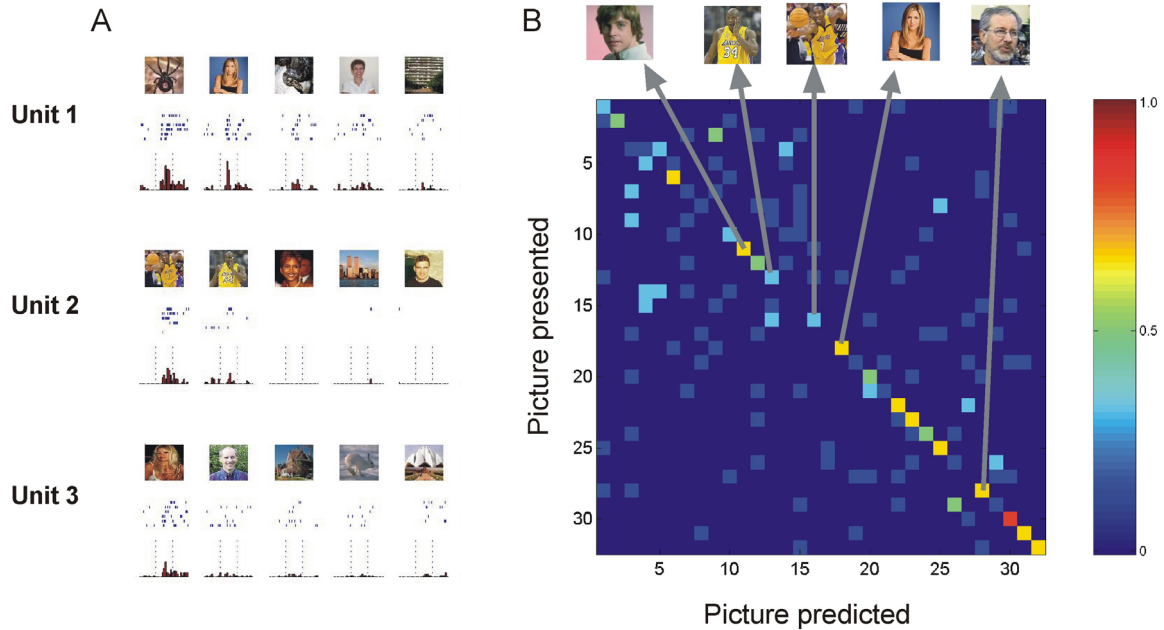


Fig. 5 Decoding of visual inputs using the firing of neurons in human medial temporal lobe

different firing pattern and the possibility of differentiating them is crucial for obtaining an optimal decoding performance [11]. Fig. 5b shows the decoding matrix for 32 responsive pictures of the 19 responsive units identified in the mentioned experiment. Overall, it was possible to predict which picture was shown in 33% of the trials, 10 times more than by chance, given a chance level of $1/32 = 3.3\%$.

7. CONCLUSIONS

In the last decade there has been spectacular progress in the field of Brain-Machine Interfaces and Neuroprosthetics. Although these results are very promising, we are still far from real applications, such as a bionic arm that could be controlled for brain signals and could help a paralyzed patient to perform every day tasks, like reaching and grasping different objects. The success of such an enterprise relies critically on an interdisciplinary approach, involving Neuroscience, Robotics, Control Theory and Engineering, among other disciplines. It also depends on the further development of methods for processing large amounts of data, like the one produced by the activity of populations of many neurons. At this respect, we described two major components of such methods, the use of fully automatic spike sorting and decoding algorithms. Besides the immense clinical potential of this field of research, advances in this area will certainly give new major insights into how our brains work and are able to perform an incredible variety of refined tasks and behaviors.

8. ACKNOWLEDGEMENTS

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